Trabajo 3

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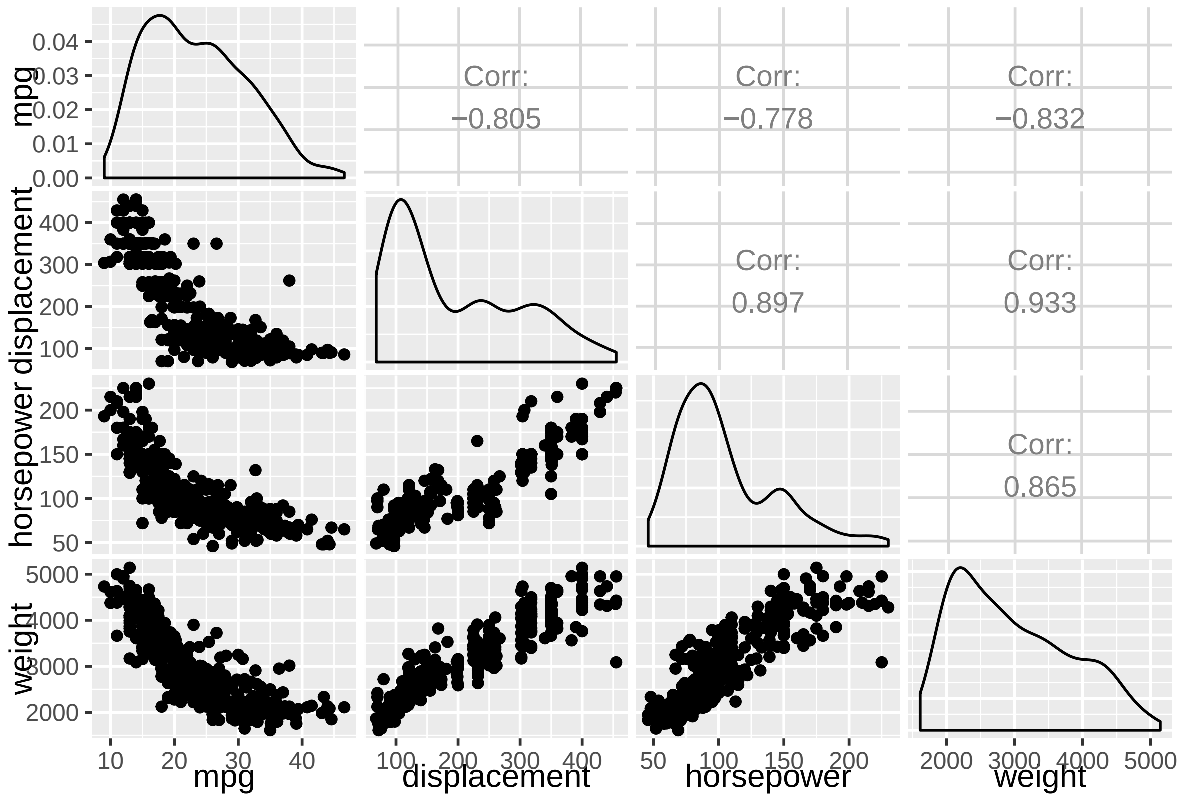
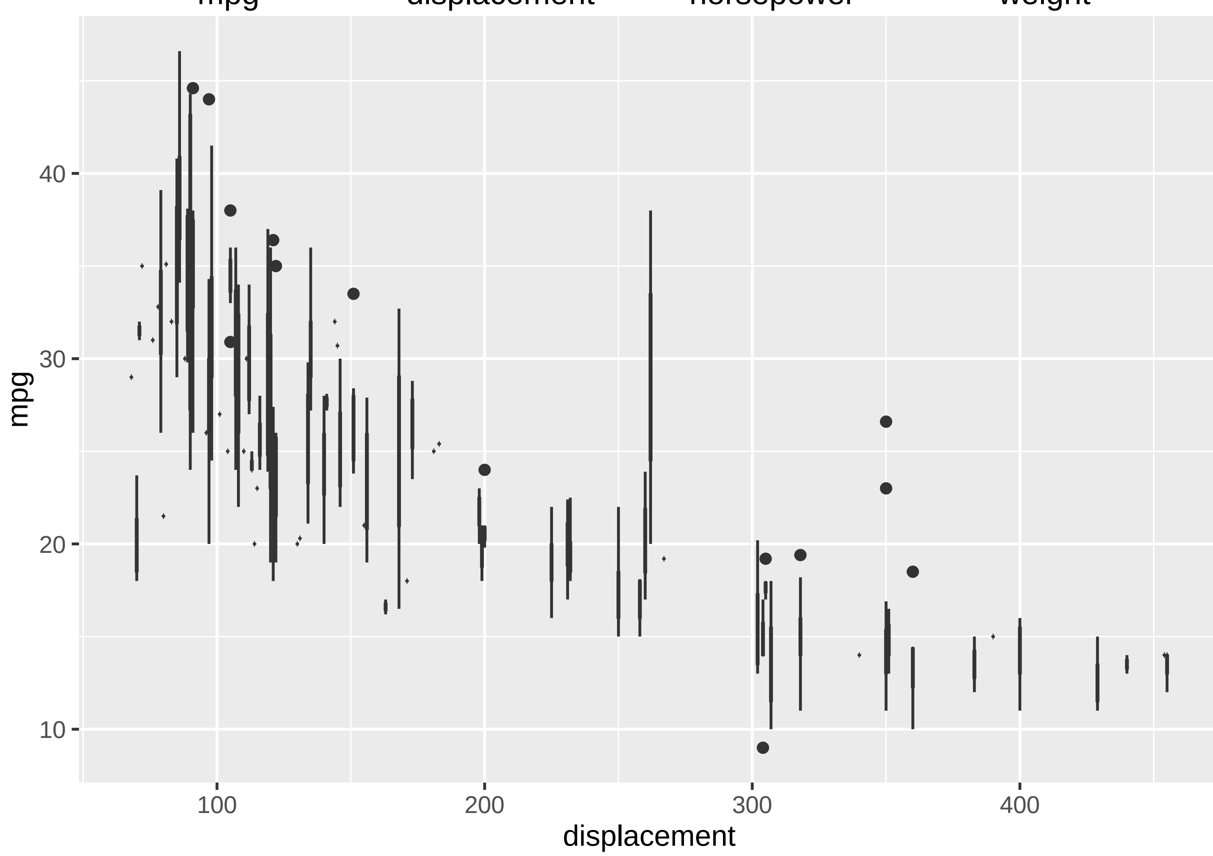
Ejercicio 1

Apartado a)

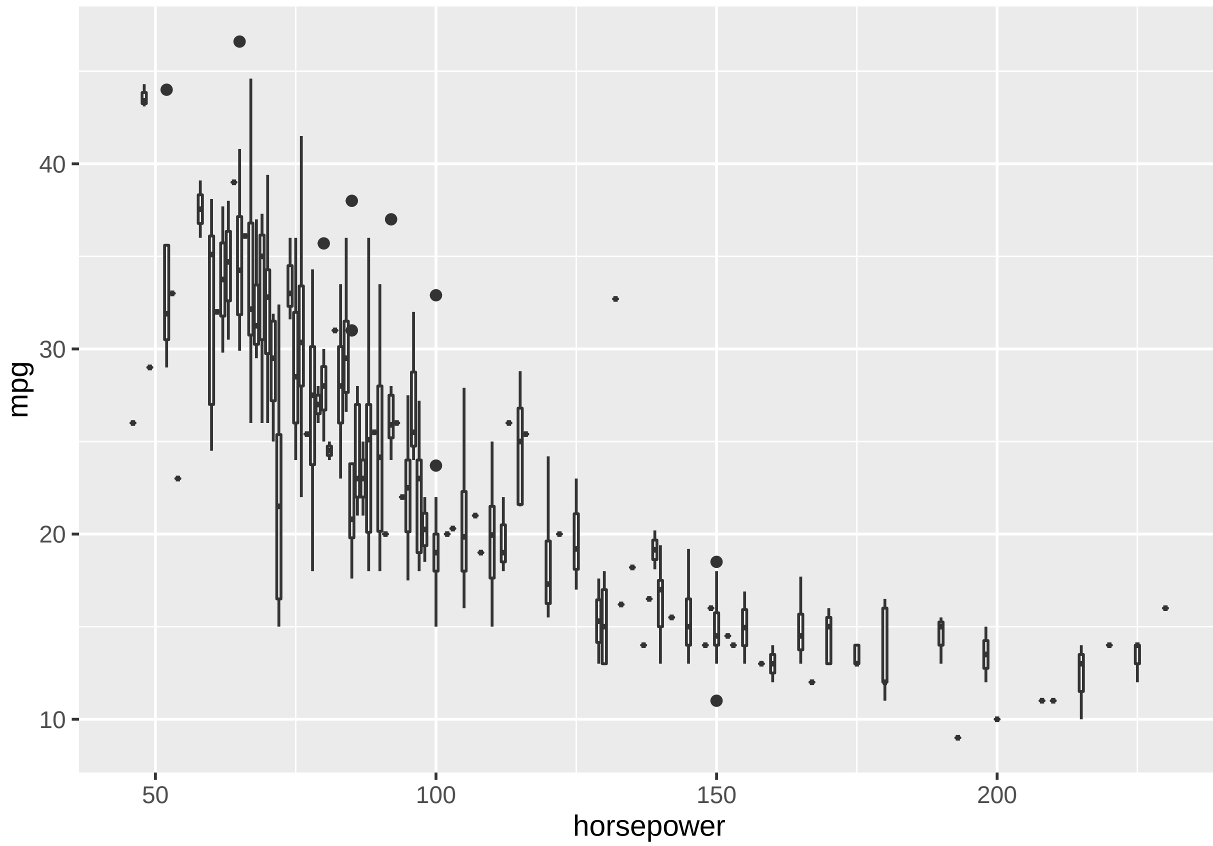
Parece ser que las variables de las que más depende *mpg* son *displacement*, *horsepower* y *weight*. Veámoslas con más detalle.



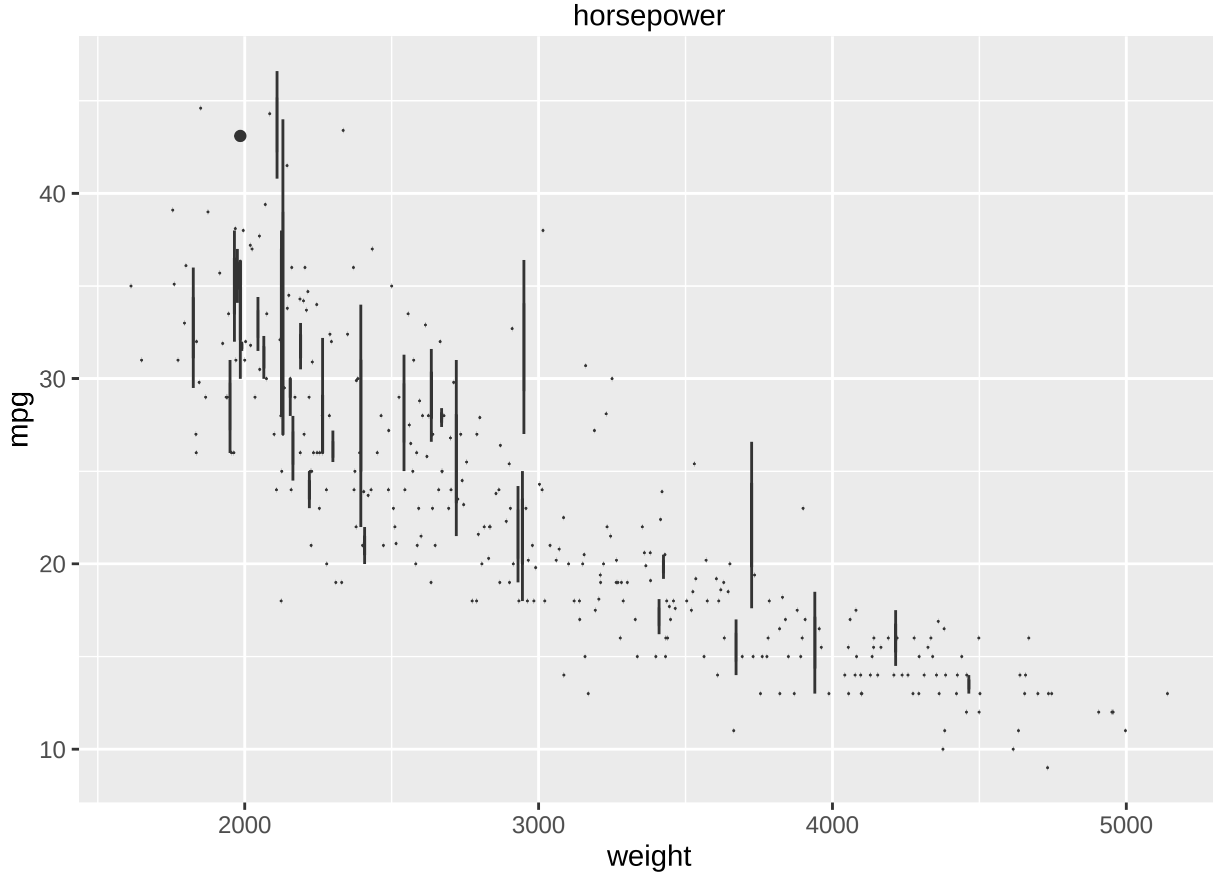
mpg
displacement
horsepower
weight
Corr:
−0.805
Corr:
−0.778
Corr:
−0.832
Corr:
0.897
Corr:
0.933
Corr:
0.865



mpg
displacement



40
30
20
10
mpg
50
100
150
200
horsepower



40
30
20
10
mpg
2000
3000
4000
5000
weight

Apartado b)

Seleccionamos las variables que hemos decidido para predecir.

```
Auto.selected <- Auto[,c("displacement","horsepower","weight")]
```

Apartado c)

Como nuestro conjunto de datos es grande (392 instancias), podemos realizar un muestreo aleatorio. Así tampoco falseamos las muestras, cosa que podría pasarnos si realizamos un muestreo estratificado.

```
index <- sample(nrow(Auto), size = 0.8*nrow(Auto) )

Auto.train <- Auto.selected[index,]
Auto.test <- Auto.selected[-index,]
```

Apartado d)

Vamos a crear una nueva variable, *mpg01*, la cual tendrá 1 si el valor de *mpg* está por encima de la mediana y -1 en otro caso.

```
mpg01 <- ifelse(Auto$mpg >= median(Auto$mpg), 1, 0)
Auto.selected$mpg01 <- mpg01
Auto.train$mpg01 <- mpg01[index]
Auto.test$mpg01 <- mpg01[-index]
```

Apartado d1)

Vamos a ajustar un modelo de regresión logística para predecir *mpg01*.

```
model.LogReg <- glm(mpg01 ~ ., data = Auto.train, family = binomial)
prediction.LogReg <- predict(model.LogReg, newdata = Auto.test)
prediction.LogReg
```

```
##           5          10          12          26          37
##  -4.04368525 -7.48368974 -5.44899213 -9.52300480 -1.42407833
##          38          44          45          48          49
##  -1.61152690 -8.67950592 -9.62774405 -1.79314656 -1.10221355
##          58          60          64          71          73
##   1.83211841  3.44739679 -8.13689797 -8.72066034 -5.28041034
##          79          80          87          90          92
##   0.64503893  3.07579492 -4.84599161 -5.20380250 -7.44172538
##          96          99         100         103         107
## -11.54802619 -1.78524803 -0.93422861  4.32005837 -7.99482997
##         108         116         122         123         124
##  -0.62618624 -5.97977326 -4.45739214  0.48112296 -0.59389526
##         125         132         137         146         152
##  -6.34601345  4.17773124 -5.41012960  3.85517658  3.69981282
##         154         155         165         167         180
##  -2.31288985 -1.13603253 -1.44956306 -3.11627459  0.32691408
##         187         198         201         202         206
##   2.51972946  3.60384424 -1.62071049 -2.85040481  2.92790375
##         219         221         224         230         235
```

```
##   4.35179380   3.64178815  -5.75035971  -7.98131760   0.74973498
##          239          243          246          249          250
##   2.80275212   0.59960079   3.92457004   4.20408780  -2.40499017
##          258          271          277          282          287
##  -1.11703835   1.13841895   0.04431415  -0.16844383  -4.21416919
##          300          318          333          341          347
##   0.54742764   2.76060074   4.06863233   0.79676274   3.37799439
##          350          353          358          359          360
##   3.56640725   2.81333105   0.93194508   1.76691942   0.16202180
##          368          372          376          378          382
##   1.43548956   1.48243855   3.48742203   3.30971798   2.80219058
##          385          388          393          397
##   3.58070768   0.86587481   0.83732702   1.33745012
```

```
error.test <- "¿Esto cómo va?"
```

El error de test de este modelo es `¿Esto cómo va?`.

Apartado d2)

Ahora vamos a ajusart un modelo k-NN.

Apartado d3)

Veamos las curvas ROC de ambos modelos.

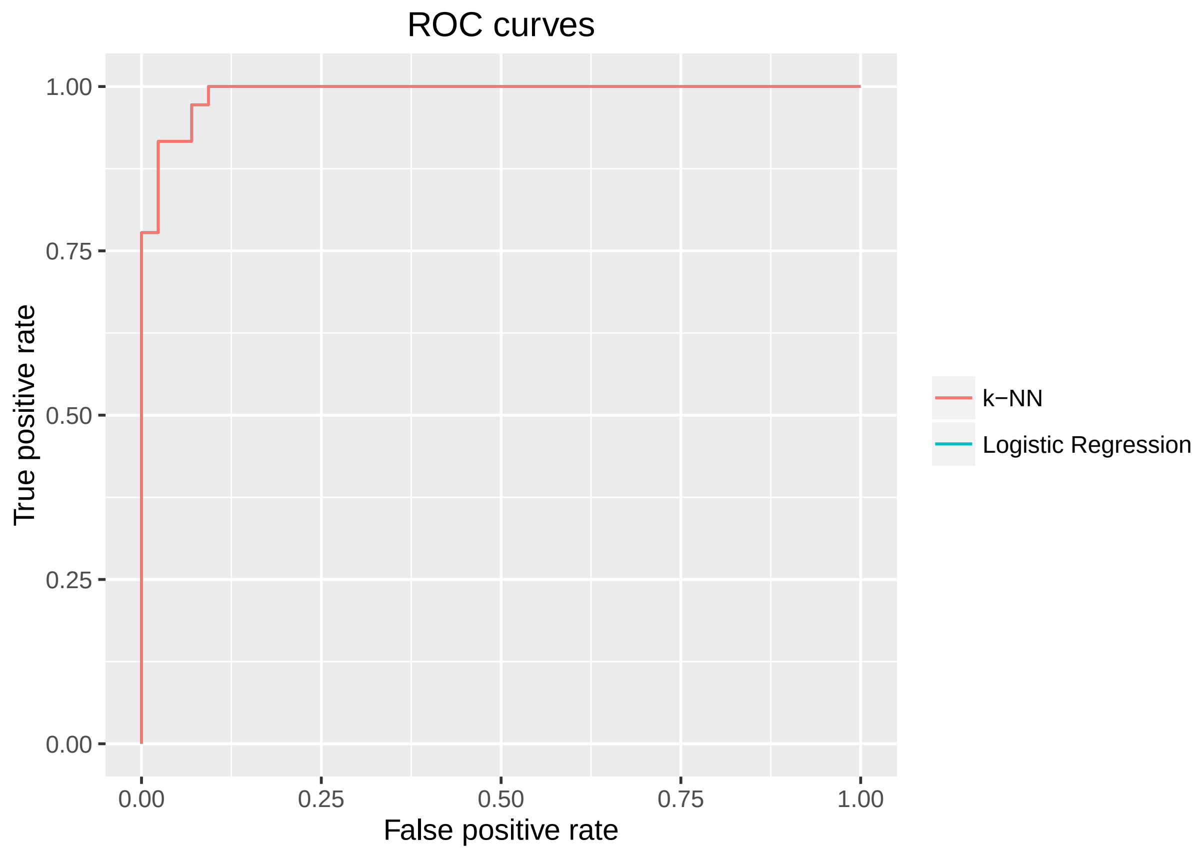
```
roc.prediction.regLog <- prediction(prediction.LogReg, Auto.test$mpg01)
roc.performance.regLog <- performance(roc.prediction.regLog, measure = "tpr", x.measure = "fpr")

### Meter del knn

####
roc.performance.knn <- roc.performance.regLog

roc.data <- data.frame(x  = roc.performance.regLog@x.values[[1]],
                       y1 = roc.performance.regLog@y.values[[1]],
                       y2 = roc.performance.knn@y.values[[1]])

ggplot(roc.data, aes(x)) +
  geom_line(aes(y = y1, colour = "Logistic Regression")) +
  geom_line(aes(y = y2, colour = "k-NN")) +
  theme(legend.title = element_blank()) +
  labs(title= "ROC curves", x = "False positive rate", y = "True positive rate")
```




```
auc.regLog  <- auc(roc.data$x,roc.data$y1, type = 'spline')
auc.knn     <- auc(roc.data$x,roc.data$y2, type = 'spline')
```

El área bajo la curva de la ROC de regresión logística es `0.9868717` y la del k-NN es `0.9868717`. Luego `k-NN` es el modelo que mejor *performance* tiene.

Apartado e) (Bonus-1)

Para estudiar el error con validación cruzada hacemos uso de `cv.glm`

```
model.full.LogReg <- glm(mpg01 ~ ., data = Auto.selected)
cv.LogReg <- cv.glm(data = Auto.selected, glmfit = model.full.LogReg, K = 5)
cv.LogReg$delta
```

```
## [1] 0.1035423 0.1033395
```

El error estimado es el primero de este vector. El segundo es un ajusto para compenar el sesgo introducido al no usar *Leave-One-Out*.

Para el caso del k-NN

Por tanto, vemos que es mejor *uno*.

Apartado f) (Bonus-2)

Por hacer

Ejercicio 2

Apartado a)

Ajustamos con validación cruzada sobre la variable *crim*, que es la que está en la posición 1.

```
attach(Boston)

index <- sample(nrow(Boston), 0.8*nrow(Boston))
Boston.full <- Boston
Boston.train <- Boston[index,]
Boston.test <- Boston[-index,]

model.Boston <- glmnet(as.matrix(Boston.train[,-1]),Boston.train[,1], alpha = 1)
```

Apartado b)

Ahora utilizamos un método LASSO y seleccionamos las variables que están por encima de un umbral.

```
cv.Boston <- cv.glmnet(as.matrix(Boston[,-1]), Boston[,1], nfolds = 5, alpha = 1)
lasso.coeff <- predict(cv.Boston, type="coefficients", s = cv.Boston$lambda.min)
threshold <- 0.1
selected <- which(abs(lasso.coeff) > threshold)[-1]
```

Con esto afirmamos que las características que superan nuestro umbral `0.1` son `4, 5, 6, 8, 9, 11, 13, 14`.

Seguir con regularización.

Apartado c)

Al igual que en el anterior apartado, definimos una nueva variable usando la mediana como umbral.

```
crim1 <- ifelse(Boston$crim > median(Boston$crim), 1, -1)
Boston.full$crim1 <- crim1
Boston.train.crim1 <- Boston.full[index,]
Boston.test.crim1 <- Boston.full[-index,]
```

Ahora ajustamos varias *SVM*, probaremos la lineal y con los núcleos disponibles, y veremos cómo se comporta cada uno. 'Ver cuál sería mejor a priori con pairs o similar'.

```
svm.linear <- svm(crim1 ~ ., data = Boston.train.crim1[,-1], kernel = "linear")
svm.linear.prediction <- predict(svm.linear, newdata = Boston.test.crim1[,-1])
# confusionMatrix(svm.linear.prediction, Boston.test$crim1)
svm.linear.prediction
```

```
##           2           3           5           9          15          31
## -0.82252184 -0.72809080 -1.00711060 -0.31060336 -0.65010314 -0.63253707
##          47          50          52          55          56          73
## -1.02462280 -0.90718580 -0.89138476 -1.12111243 -1.06478406 -0.97076519
##          80          88          90          94          95          97
## -0.65501325 -1.10169183 -0.95948355 -0.48362314 -0.34723009 -1.15557372
##         110         115         117         120         122         125
## -0.57850164 -0.34903447 -0.34292145 -0.39308417  0.36498117  0.39714707
##         132         133         141         142         146         152
```

```
##  0.37566582  0.41862995  0.33566793  0.38481647  1.12646434  1.07520224
##         153         157         162         183         187         191
##  0.81077434  1.04963182  0.77379481 -0.80470863 -0.76717346 -0.79011222
##         199         201         204         206         211         212
## -0.90513924 -1.09438929 -0.72165449 -0.74404814 -0.63046993 -0.65598160
##         219         220         221         223         232         238
## -0.21337449 -0.21782429 -0.63465795 -0.65556938 -0.45988401 -0.47276188
##         240         251         253         258         268         270
## -0.90294523 -0.97838389 -0.90757548  0.08261912 -0.14504616 -1.04933618
##         279         284         286         290         302         305
## -0.88052403 -1.06274533 -1.25591606 -0.92761107 -0.79337605 -0.87075103
##         309         318         325         330         341         342
## -0.44492390 -0.47029723 -0.81292835 -1.10010344 -0.92749404 -1.01143364
##         345         354         356         359         360         370
## -0.79294331 -0.95419970 -1.32627595  1.08728465  1.23551558  1.10184136
##         376         377         382         386         390         391
##  0.96587257  0.97908812  0.94350282  0.98293677  0.99942824  1.03069118
##         393         394         395         397         404         411
##  0.98702676  0.97905053  0.97201087  0.99721490  0.92536606  0.85044175
##         415         416         421         423         429         431
##  1.06753281  1.05477456  1.12650835  0.87409773  0.96825447  0.80279720
##         432         440         443         445         446         455
##  0.84750299  1.11024204  1.18760188  1.14445048  1.21544873  1.18541683
##         461         467         470         471         474         494
##  1.11697821  1.04469147  0.66749769  0.78164150  0.92116178 -0.40447905
```

```r
svm.polynomial <- svm(crim1 ~ ., data = Boston.train.crim1[,-1], kernel = "polynomial")
svm.polynomial.prediction <- predict(svm.polynomial, newdata = Boston.test.crim1[,-1])
# confusionMatrix(svm.polynomial.prediction, Boston.test$crim1)
svm.polynomial.prediction
```

```
##           2           3           5           9          15          31
## -0.94192116 -0.78806401 -0.84563645 -1.29723268 -0.60896262 -0.17472712
##          47          50          52          55          56          73
## -0.94238126 -0.97498086 -1.10735982 -1.13042213 -0.88473260 -0.97927064
##          80          88          90          94          95          97
## -0.77262743 -0.95726196 -0.99724612 -0.76471872 -0.76020115 -0.98326960
##         110         115         117         120         122         125
## -0.62956552 -0.70863331 -0.69608959 -0.69372255 -0.75778015 -0.58178394
##         132         133         141         142         146         152
## -0.44166134 -0.45229355 -0.17726954  0.06165511  0.92086864  1.13110871
##         153         157         162         183         187         191
##  0.16622200  0.90093560  1.05959378 -1.02002098 -0.01299808 -0.98606316
##         199         201         204         206         211         212
## -0.97764140 -0.94044625 -1.06725491 -0.77577936  0.41204440  0.23930236
##         219         220         221         223         232         238
##  0.33188924  0.40249161  0.85036421  0.55033193 -0.51829848 -0.51542943
##         240         251         253         258         268         270
## -0.91667742 -0.95912467 -0.76785795  1.88475078  0.99643027 -0.62262924
##         279         284         286         290         302         305
## -0.83563045 -3.97086788 -1.31785433 -0.80444604 -0.83195348 -0.79561371
##         309         318         325         330         341         342
## -0.75491526 -0.69949395 -0.82432723 -1.06434090 -0.79375096 -1.24754722
##         345         354         356         359         360         370
## -0.78566338 -0.81240139 -1.02763557  0.75762202  1.01724944  1.01908132
```

```
##         376        377        382        386        390        391
##  0.94906323  0.95879864  0.93649533  0.98728092  1.06059927  1.04613189
##         393        394        395        397        404        411
##  1.05926079  1.01227700  1.03436225  0.98561183  1.03473008  1.05672427
##         415        416        421        423        429        431
##  0.83674976  1.02781360  0.99803109  0.94879954  0.98977352  0.90342485
##         432        440        443        445        446        455
##  0.90568332  1.15399655  1.01293123  1.09430075  1.09120657  1.01024031
##         461        467        470        471        474        494
##  0.97163969  0.90375439  1.01096260  0.89050279  0.93608024 -0.68306846
```

```
svm.radial <- svm(crim1 ~ ., data = Boston.train.crim1[,-1], kernel = "radial")
svm.radial.prediction <- predict(svm.radial, newdata = Boston.test.crim1[,-1])
# confusionMatrix(svm.radial.prediction, Boston.test$crim1)
svm.radial.prediction
```

```
##           2           3           5           9          15          31
## -0.96593935 -0.74014673 -0.83585347 -0.86079950  0.10763094  0.97879142
##          47          50          52          55          56          73
## -0.97735549 -0.96654562 -1.18240251 -0.75787351 -0.84207195 -0.93515272
##          80          88          90          94          95          97
## -0.89763344 -1.16366669 -1.03370327 -0.88161249 -0.72991190 -1.25316314
##         110         115         117         120         122         125
## -0.29044028 -0.64300194 -0.71923508 -0.62300775  0.08470164  0.28746113
##         132         133         141         142         146         152
##  0.73279844  0.64937482  0.83744311  0.66915044  0.79055297  1.11414967
##         153         157         162         183         187         191
##  0.81872438  0.76610374  1.02837168 -0.69519688 -0.02803858 -0.94125079
##         199         201         204         206         211         212
## -0.97192757 -0.88391907 -0.96306469 -0.85759326  0.48948645  0.61291554
##         219         220         221         223         232         238
##  0.66610401  0.55883880  0.47498146  0.27616039 -0.18195290 -0.24577100
##         240         251         253         258         268         270
## -1.09648990 -0.97262598 -0.66911847  1.08410339  0.81708152 -0.25173409
##         279         284         286         290         302         305
## -1.08069222 -0.55967491 -1.04215020 -1.03245544 -1.06625820 -0.91325980
##         309         318         325         330         341         342
## -0.57701814 -0.40744934 -0.96842649 -0.96470276 -0.57161193 -1.05888848
##         345         354         356         359         360         370
## -0.96346872 -0.62397108 -0.87881765  0.93701086  1.05080023  0.93173460
##         376         377         382         386         390         391
##  0.90949453  0.94308231  0.94841143  0.93217978  0.99286737  1.03419667
##         393         394         395         397         404         411
##  0.98087457  0.98618162  0.98678216  0.98802273  0.93964003  0.80051696
##         415         416         421         423         429         431
##  0.83972788  0.90785798  1.06413284  1.04557818  1.01216337  0.95396023
##         432         440         443         445         446         455
##  0.91142396  1.03134551  1.06703788  1.03962790  0.96338609  0.92000864
##         461         467         470         471         474         494
##  1.08293144  0.99575619  0.89954051  0.97275270  1.01153053 -0.41844807
```

```
svm.sigmoid <- svm(crim1 ~ ., data = Boston.train.crim1[,-1], kernel = "sigmoid")
svm.sigmoid.prediction <- predict(svm.sigmoid, newdata = Boston.test.crim1[,-1])
# confusionMatrix(svm.sigmoid.prediction, Boston.test$crim1)
svm.sigmoid.prediction
```

```
##           2           3           5           9          15
##  -0.05945781 -0.74035688 -3.29148884 -3.95870979 -2.21952959
##          31          47          50          52          55
##  -7.00574408 -0.60282240 -1.16406446  1.14832797  5.98342552
##          56          73          80          88          90
## -15.96743858  0.72668613  0.04106608 -0.52991545 -0.02886361
##          94          95          97         110         115
##   4.59546721  3.83874296 -1.14818566 -3.73697867 -2.04687325
##         117         120         122         125         132
##  -1.45442104 -2.26368625 -0.42289140 -1.12929415  0.57145123
##         133         141         142         146         152
##   0.62016954  0.81601218  6.00879382 -5.32884132 -3.21365465
##         153         157         162         183         187
##  -6.00512167 -5.17549212 10.94711347  1.79531114 -2.05154228
##         191         199         201         204         206
##  -7.49981630 -16.03488215 -13.16570482 -18.13622075  0.40955487
##         211         212         219         220         221
##  -1.01986854 -3.94679757 -1.52904791  1.75056916  1.66247828
##         223         232         238         240         251
##   1.99518343  0.65047796  0.61356533 -0.90782245  0.07637239
##         253         258         268         270         279
##  -4.05286330  9.42135654  4.42726858  4.39898716  1.18377126
##         284         286         290         302         305
## -19.11848748 -5.05063078 -3.30160561  0.38396171 -1.29092787
##         309         318         325         330         341
##   1.22109437 -1.88759862  0.56171033 -1.16946099 -1.02185250
##         342         345         354         356         359
##  -7.82995406 -2.29635587 -15.62018211  2.80066557 -5.35268726
##         360         370         376         377         382
##  -0.30298211 -2.76560278 -3.29679334  1.46364829  2.14391814
##         386         390         391         393         394
##  11.91427764  7.00035325  3.50132839  9.88493413  1.01838333
##         395         397         404         411         415
##   2.85696579  1.97857328  6.90633420  1.48625580 18.59697191
##         416         421         423         429         431
##   9.32104354  0.49278115 -1.19661726  3.35020638 -1.16459688
##         432         440         443         445         446
##  -1.44300697  6.91653071  1.77839795  7.87140145  6.92099424
##         455         461         467         470         471
##   2.26214613 -1.30574793  0.81052246 -3.73009159 -3.31998240
##         474         494
##  -4.99372860 -1.26422621
```

Analizar el error.

Apartado d) (Bonus-3)

Ajustamos con validación cruzada sobre la variable *crim*.

```
cv.Boston <- cv.glmnet(as.matrix(Boston[,-1]), Boston[,1], nfolds = 5, alpha = 1)
```

El error de validación cruzada (respondiendo al Bonus-3) es

```
cv.Boston$cvm
```

```
##  [1] 73.18910 70.02364 66.63692 63.22860 60.39827 58.04786 56.09593
##  [8] 54.47489 53.01730 51.70605 50.56053 49.54884 48.68732 47.98180
## [15] 47.40236 46.92175 46.52106 46.18694 45.90859 45.67129 45.45625
## [22] 45.24990 45.05418 44.88901 44.74981 44.63289 44.53279 44.44685
## [29] 44.37432 44.30845 44.24058 44.14885 44.04908 43.94954 43.86372
## [36] 43.80016 43.75173 43.69488 43.62922 43.55415 43.47634 43.41514
## [43] 43.36609 43.32745 43.28323 43.23711 43.20371 43.17616 43.15469
## [50] 43.13743 43.12356 43.11371 43.10480 43.09708 43.09161 43.08766
## [57] 43.07883 43.07458 43.06981 43.06786 43.06547 43.06394 43.06274
## [64] 43.06208 43.06249 43.06266 43.06300 43.06391 43.06457 43.06525
## [71] 43.06684 43.06781 43.06850 43.06953 43.07003 43.07066
```

Completar solución.

Ejercicio 3

Apartado a)

Ya tenemos cargado y separado el conjunto de datos en 80% training y 20% test.

Apartado b)

Vamos a ajusar un modelo de Bagging. Para ello usaremos el RandomForest y le diremos que use el total de características disponibles.

```
bagging <- randomForest(medv ~., data = Boston, subset = -index, mtray = ncol(Boston)-1, importance = TR
bagging.prediction <- predict(bagging, newdata = Boston.test)
bagging.error <- "¿Esto cómo es?"
```

El error de test del modelo bagging es `¿Esto cómo es?`.

Apartado c)

Ahora vamos a ajustar un RandomForest.

```
randomFor <- randomForest(medv ~., data = Boston, subset = -index, importance = TRUE)

randomFor.error <- "¿Esto cómo es?"
```

El número de árboles usado es `500`. El error de test es `¿Esto cómo es?`.

La diferencia con bagging es …

Apartado d)

Ajustamos un modelo de regresión con Boosting.

```
boosting <- gbm(medv~., data = Boston.train, distribution = "gaussian")
pred <- predict(boosting, Boston.test, n.trees = 100)
boosting.error <- "¿Esto cómo es?"
```

El error de test es `¿Esto cómo es?`.

La diferencia con bagging y randomForest es…

Ejercicio 4

```
attach(OJ)
```

Apartado a)

Cogemos una muestra aleatoria de 800 elementos y lo usamos como training.

```
index <- sample(nrow(OJ), 800)
OJ.train <- OJ[index,]
OJ.test <- OJ[-index,]
```

Ajustamos un árbol con la variable *Purchase* como objetivo.

```
model.tree <- tree(Purchase ~ ., data = OJ.train)
```

Apartado b)

Veamos un resumen del árbol.

```
summary(model.tree)
```

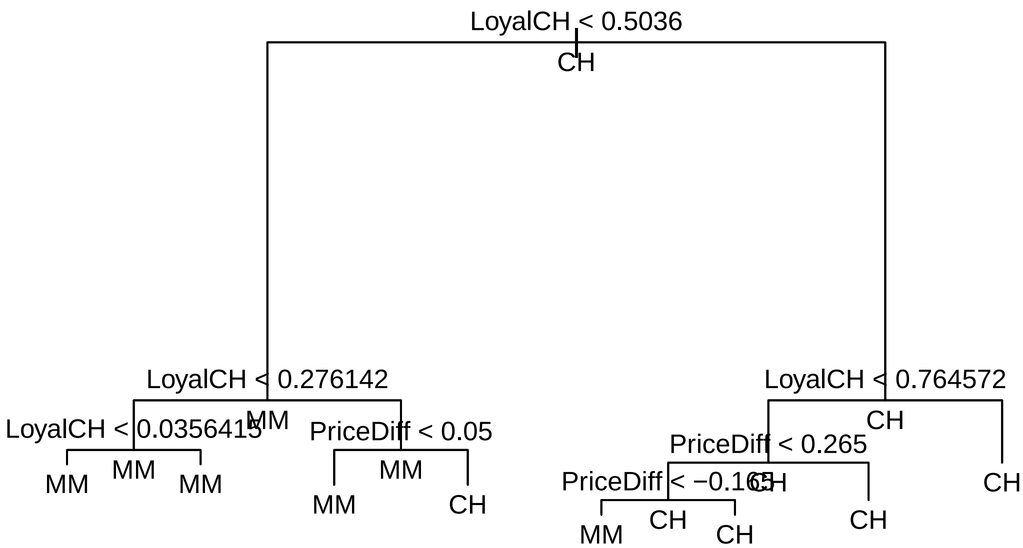
```
##
## Classification tree:
## tree(formula = Purchase ~ ., data = OJ.train)
## Variables actually used in tree construction:
## [1] "LoyalCH"   "PriceDiff"
## Number of terminal nodes:  8
## Residual mean deviance:  0.7551 = 598 / 792
## Misclassification error rate: 0.1638 = 131 / 800
```

El número de nodos terminales es de 8, y tiene un error del 16.38%. Completar.

Apartado c)

Dibujamos el árbol obtenido.

```
plot(model.tree, main="Classification tree")
text(model.tree, all=TRUE, cex=.8)
```



Interpretar.

Apartado d)

Aplicamos el árbol a nuestros datos de test.

```
prediction.tree <- predict(model.tree, OJ.test)
prediction.tree
```

```
##             CH         MM
## 2    0.69767442 0.30232558
## 9    0.96456693 0.03543307
## 13   0.96456693 0.03543307
## 14   0.94444444 0.05555556
## 20   0.59433962 0.40566038
## 21   0.94444444 0.05555556
## 22   0.94444444 0.05555556
## 38   0.96456693 0.03543307
## 39   0.20987654 0.79012346
## 43   0.96456693 0.03543307
## 44   0.96456693 0.03543307
## 49   0.96456693 0.03543307
## 52   0.69767442 0.30232558
## 53   0.96456693 0.03543307
## 54   0.96456693 0.03543307
## 56   0.94444444 0.05555556
## 59   0.96456693 0.03543307
## 62   0.96456693 0.03543307
## 64   0.69767442 0.30232558
## 68   0.69767442 0.30232558
## 70   0.33333333 0.66666667
## 74   0.96456693 0.03543307
## 77   0.96456693 0.03543307
## 78   0.96456693 0.03543307
## 83   0.96456693 0.03543307
## 88   0.69767442 0.30232558
```

```
## 90   0.96456693 0.03543307
## 91   0.59433962 0.40566038
## 93   0.59433962 0.40566038
## 96   0.69767442 0.30232558
## 98   0.69767442 0.30232558
## 102  0.96456693 0.03543307
## 109  0.96456693 0.03543307
## 110  0.96456693 0.03543307
## 112  0.96456693 0.03543307
## 118  0.96456693 0.03543307
## 121  0.96456693 0.03543307
## 125  0.96456693 0.03543307
## 126  0.96456693 0.03543307
## 128  0.96456693 0.03543307
## 137  0.96456693 0.03543307
## 144  0.20987654 0.79012346
## 151  0.18260870 0.81739130
## 166  0.96456693 0.03543307
## 167  0.96456693 0.03543307
## 168  0.96456693 0.03543307
## 171  0.96456693 0.03543307
## 178  0.96456693 0.03543307
## 179  0.96456693 0.03543307
## 191  0.96456693 0.03543307
## 200  0.96456693 0.03543307
## 201  0.96456693 0.03543307
## 203  0.94444444 0.05555556
## 211  0.96456693 0.03543307
## 219  0.96456693 0.03543307
## 223  0.18260870 0.81739130
## 225  0.59433962 0.40566038
## 226  0.59433962 0.40566038
## 228  0.59433962 0.40566038
## 235  0.69767442 0.30232558
## 243  0.96456693 0.03543307
## 246  0.96456693 0.03543307
## 248  0.96456693 0.03543307
## 250  0.96456693 0.03543307
## 251  0.96456693 0.03543307
## 253  0.96456693 0.03543307
## 271  0.59433962 0.40566038
## 272  0.20987654 0.79012346
## 275  0.01785714 0.98214286
## 277  0.01785714 0.98214286
## 279  0.01785714 0.98214286
## 292  0.01785714 0.98214286
## 294  0.01785714 0.98214286
## 297  0.20987654 0.79012346
## 299  0.59433962 0.40566038
## 304  0.59433962 0.40566038
## 311  0.59433962 0.40566038
## 317  0.96456693 0.03543307
## 318  0.94444444 0.05555556
## 321  0.69767442 0.30232558
```

```
## 322  0.69767442 0.30232558
## 328  0.69767442 0.30232558
## 333  0.18260870 0.81739130
## 338  0.18260870 0.81739130
## 346  0.96456693 0.03543307
## 347  0.96456693 0.03543307
## 348  0.96456693 0.03543307
## 352  0.96456693 0.03543307
## 354  0.33333333 0.66666667
## 359  0.59433962 0.40566038
## 363  0.20987654 0.79012346
## 367  0.59433962 0.40566038
## 371  0.20987654 0.79012346
## 375  0.59433962 0.40566038
## 377  0.18260870 0.81739130
## 378  0.18260870 0.81739130
## 385  0.18260870 0.81739130
## 389  0.18260870 0.81739130
## 397  0.18260870 0.81739130
## 398  0.59433962 0.40566038
## 407  0.20987654 0.79012346
## 410  0.59433962 0.40566038
## 422  0.01785714 0.98214286
## 426  0.33333333 0.66666667
## 431  0.18260870 0.81739130
## 433  0.20987654 0.79012346
## 434  0.33333333 0.66666667
## 435  0.20987654 0.79012346
## 436  0.59433962 0.40566038
## 438  0.20987654 0.79012346
## 440  0.59433962 0.40566038
## 444  0.96456693 0.03543307
## 452  0.59433962 0.40566038
## 461  0.59433962 0.40566038
## 463  0.69767442 0.30232558
## 464  0.94444444 0.05555556
## 466  0.96456693 0.03543307
## 467  0.96456693 0.03543307
## 469  0.96456693 0.03543307
## 470  0.96456693 0.03543307
## 474  0.59433962 0.40566038
## 475  0.18260870 0.81739130
## 480  0.94444444 0.05555556
## 483  0.94444444 0.05555556
## 486  0.94444444 0.05555556
## 489  0.96456693 0.03543307
## 493  0.96456693 0.03543307
## 497  0.20987654 0.79012346
## 506  0.96456693 0.03543307
## 510  0.96456693 0.03543307
## 517  0.96456693 0.03543307
## 519  0.59433962 0.40566038
## 524  0.59433962 0.40566038
## 529  0.69767442 0.30232558
```

```
## 532  0.69767442 0.30232558
## 533  0.94444444 0.05555556
## 541  0.59433962 0.40566038
## 542  0.59433962 0.40566038
## 546  0.18260870 0.81739130
## 547  0.18260870 0.81739130
## 549  0.18260870 0.81739130
## 551  0.18260870 0.81739130
## 554  0.18260870 0.81739130
## 555  0.18260870 0.81739130
## 559  0.20987654 0.79012346
## 565  0.94444444 0.05555556
## 567  0.20987654 0.79012346
## 569  0.59433962 0.40566038
## 570  0.59433962 0.40566038
## 571  0.18260870 0.81739130
## 582  0.94444444 0.05555556
## 584  0.96456693 0.03543307
## 585  0.96456693 0.03543307
## 586  0.96456693 0.03543307
## 592  0.94444444 0.05555556
## 596  0.96456693 0.03543307
## 598  0.96456693 0.03543307
## 599  0.96456693 0.03543307
## 600  0.96456693 0.03543307
## 602  0.96456693 0.03543307
## 607  0.96456693 0.03543307
## 608  0.96456693 0.03543307
## 610  0.96456693 0.03543307
## 611  0.94444444 0.05555556
## 615  0.69767442 0.30232558
## 619  0.96456693 0.03543307
## 621  0.96456693 0.03543307
## 624  0.96456693 0.03543307
## 646  0.69767442 0.30232558
## 648  0.96456693 0.03543307
## 657  0.96456693 0.03543307
## 659  0.96456693 0.03543307
## 660  0.96456693 0.03543307
## 668  0.20987654 0.79012346
## 674  0.69767442 0.30232558
## 690  0.18260870 0.81739130
## 691  0.01785714 0.98214286
## 692  0.01785714 0.98214286
## 693  0.01785714 0.98214286
## 700  0.01785714 0.98214286
## 705  0.01785714 0.98214286
## 711  0.01785714 0.98214286
## 712  0.01785714 0.98214286
## 723  0.01785714 0.98214286
## 724  0.01785714 0.98214286
## 732  0.20987654 0.79012346
## 737  0.20987654 0.79012346
## 738  0.59433962 0.40566038
```

```
## 743  0.94444444 0.05555556
## 745  0.33333333 0.66666667
## 747  0.33333333 0.66666667
## 752  0.59433962 0.40566038
## 768  0.96456693 0.03543307
## 771  0.20987654 0.79012346
## 772  0.59433962 0.40566038
## 776  0.69767442 0.30232558
## 779  0.59433962 0.40566038
## 785  0.18260870 0.81739130
## 786  0.18260870 0.81739130
## 789  0.59433962 0.40566038
## 791  0.59433962 0.40566038
## 802  0.59433962 0.40566038
## 803  0.94444444 0.05555556
## 806  0.94444444 0.05555556
## 810  0.96456693 0.03543307
## 812  0.96456693 0.03543307
## 813  0.96456693 0.03543307
## 816  0.96456693 0.03543307
## 820  0.96456693 0.03543307
## 821  0.96456693 0.03543307
## 823  0.96456693 0.03543307
## 824  0.96456693 0.03543307
## 825  0.96456693 0.03543307
## 830  0.96456693 0.03543307
## 831  0.96456693 0.03543307
## 833  0.18260870 0.81739130
## 837  0.59433962 0.40566038
## 851  0.96456693 0.03543307
## 854  0.96456693 0.03543307
## 859  0.96456693 0.03543307
## 865  0.59433962 0.40566038
## 868  0.69767442 0.30232558
## 871  0.69767442 0.30232558
## 873  0.33333333 0.66666667
## 876  0.94444444 0.05555556
## 877  0.94444444 0.05555556
## 878  0.96456693 0.03543307
## 882  0.96456693 0.03543307
## 893  0.94444444 0.05555556
## 896  0.96456693 0.03543307
## 899  0.96456693 0.03543307
## 906  0.18260870 0.81739130
## 916  0.59433962 0.40566038
## 918  0.69767442 0.30232558
## 924  0.33333333 0.66666667
## 928  0.18260870 0.81739130
## 937  0.18260870 0.81739130
## 940  0.18260870 0.81739130
## 944  0.01785714 0.98214286
## 949  0.01785714 0.98214286
## 950  0.01785714 0.98214286
## 954  0.01785714 0.98214286
```

```
## 958  0.20987654 0.79012346
## 961  0.18260870 0.81739130
## 965  0.33333333 0.66666667
## 966  0.59433962 0.40566038
## 975  0.18260870 0.81739130
## 978  0.18260870 0.81739130
## 980  0.18260870 0.81739130
## 984  0.59433962 0.40566038
## 998  0.94444444 0.05555556
## 999  0.94444444 0.05555556
## 1000 0.33333333 0.66666667
## 1007 0.18260870 0.81739130
## 1008 0.18260870 0.81739130
## 1009 0.20987654 0.79012346
## 1012 0.69767442 0.30232558
## 1016 0.96456693 0.03543307
## 1022 0.94444444 0.05555556
## 1023 0.94444444 0.05555556
## 1024 0.94444444 0.05555556
## 1025 0.94444444 0.05555556
## 1027 0.96456693 0.03543307
## 1051 0.94444444 0.05555556
## 1056 0.20987654 0.79012346
## 1057 0.18260870 0.81739130
## 1061 0.69767442 0.30232558
## 1064 0.59433962 0.40566038
## 1066 0.94444444 0.05555556
## 1070 0.94444444 0.05555556
```

Valorar resultados.

Apartado e)

Aplicamos la función cv.tree() a los datos de training y veamos qué hace.

```r
model.cv.tree <- cv.tree(model.tree, K = 5)
model.cv.tree
```

```
## $size
## [1] 8 7 6 5 4 3 2 1
##
## $dev
## [1]  685.9367  675.8103  675.8103  741.2312  748.6098  791.8806  791.0690
## [8] 1074.7256
##
## $k
## [1]      -Inf  11.90930  12.21236  28.93961  31.07276  41.24425  51.79661
## [8] 297.42355
##
## $method
## [1] "deviance"
##
## attr(,"class")
## [1] "prune"         "tree.sequence"
```

Apartado f) (Bonus-4)